

Detection of missing components on a PCB using image processing

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Abstract: Manual inspection of PCB components is often inaccurate and inefficient due to human error, posing a significant risk to quality control in electronic systems. This study used YOLOv8, a state-of-the-art object detection model, for PCB inspections. The system, known for its speed and accuracy, achieved an impressive 98.3% accuracy rate across 773 instances on six component classes. The system performance was evaluated under various conditions, with 98% accuracy under ideal conditions and 96% under non-ideal conditions. Error rates rose from 1% in ideal conditions to 3% in non-ideal conditions, indicating their sensitivity to environmental factors. Feedback from students, technicians, and instructors praised the system's potential, with mean rating of 4.8 for accuracy, 4.7 for functionality, 4.8 for reliability, and 4.7 for user-friendliness. The results reveal that the system is a reliable tool for PCB verification. However, optimal camera resolution and size limits are crucial for effective inspections and component identification. This research is potential to significantly enhance efficiency and accuracy in quality control processes within the electronics manufacturing industry.

Keywords: electronic components; accuracy; YOLO; PCB; object detection

1. Introduction

Printed Circuit Boards (PCBs) are fundamental in electronics, serving as the platform that connects various components like chips, transistors, and capacitors using conductor paths typically made of copper [1]. Their construction involves materials such as fiberglass and composite epoxy, making quality essential for the optimal functioning of electronic circuits [2]. However, defects can occur during manufacturing, emphasizing the necessity for effective defect detection methods to ensure reliability and performance. While significant advancements have been made in the field of object detection, achieving high accuracy and speed remains a challenge, particularly for computers compared to human visual recognition capabilities [3]. Current defect detection techniques in PCB manufacturing had traditionally relied on manual inspection and functional testing, which, despite being thorough, are time-consuming and susceptible to human error [4], [5]. More recent approaches utilize image processing methods but still struggle to maintain efficiency during quality inspections [6].

Machine vision detection has emerged as a more effective contemporary solution. It employs digital image processing to compare test images against standards for accurate defect identification [7]. The You Only Look Once (YOLO) v3 framework enhances the speed of component detection on PCBs, utilizing artificial intelligence for real-time object detection [8]. YOLO v3 incorporates "feature pyramid networks" for detecting objects at multiple scales, thus significantly improving detection performance [9], [10], [11], [12].

Research suggests that the application of YOLO v3 in detecting missing components on PCBs can efficiently classify whether a board is functional or defective [13]. This method combines image preprocessing and the YOLO v3 network to ensure high accuracy in defect detection, benefiting both educational and industrial contexts. By refining defect detection processes, this approach enhances learning experiences and improves efficiency while minimizing errors in quality control, ultimately accelerating production speeds in PCB manufacturing. In this paper, we propose a PCB detection of missing components or two types of detection, depending on whether the PCB is good or defective. The study was made available for individuals to test in the design of electronic circuits for educational reasons. The method is based on image processing and Yolo to make it real time to detect the defective PCB. The image is pre-processed and then defect detection is performed through the Yolo network while a certain detection accuracy is ensured [14]. This approach not only enhances individuals' learning experience but also has practical applications in the industry for improving efficiency and reducing errors in quality control processes. This time, the individual's level up the speed of detection. The Researchers carried out a survey among Electronics Instructors at the University of Science and Technology of Southern Philippines, as well as electronics shops throughout Cagayan de Oro City. The survey results are shown in Figure 1.

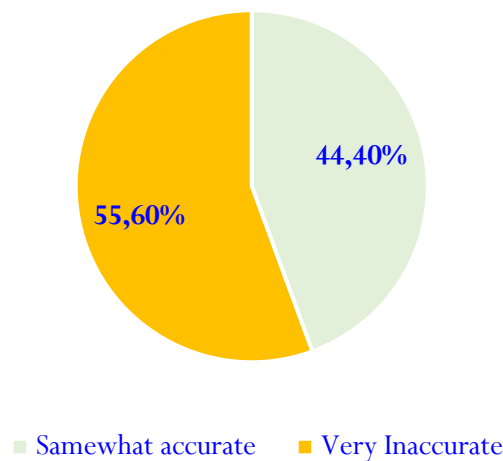


Figure 1. Accuracy of current methods

The survey shows that 44.44% of respondents have a bachelor's degree or higher, with 33.33% holding a master's degree. 66.67% are familiar with image processing for detecting missing components on PCBs, but 77.78% feel uncertain. Manual visual inspection and x-ray inspection are the most common methods, but 55.56% rate them inaccurate due to human error and time. Image processing has potential for improved detection accuracy.

As individuals test the electronic circuit on the PCB, it's more crucial in terms of quality control. Manual inspections are time-consuming and prone to human error. Although there are more methods for detecting defects in PCB circuits PCB missing components can cause serious problems for technology, ranging from broken-down systems to total malfunctions [15]. Based on our survey results, the common denominator among the problems faced by many electronics-field-related individuals is the inaccurate and inefficient manual testing of PCB components due to human error.

This research aims to develop an image processing system for accurately predicting PCB circuit correctness, focusing on detecting PCB components like flip-flops, full-wave rectifiers, half-wave rectifiers, and pre-amplifiers. This research will pursue the following goals:

- 1) To design and develop a YOLO-based object detection system that can precisely and accurately differentiate between various components and detect missing components in complex PCB layouts.
- 2) To design and develop a user-friendly Graphical User Interface (GUI) that allows users to select the specific PCB circuit for detection.
- 3) To evaluate the effectiveness of the object detection model in detecting or identifying missing components.
- 4) To assess the system’s ability to correctly identify the selected PCB circuit by comparing detected components with a predefined ground truth list.

This study focuses on improving the identification of missing PCB circuit components using image processing, thereby enhancing the efficiency of solution inspections. It will benefit individuals, particularly students at the University of Science and Technology of Southern Philippines-CDO campus, who can use the findings for lab exercises and research projects. Additionally, instructors can utilize the study's findings for educational purposes, enhancing their workload in identifying missing PCB circuit components. The application will be developed and tested in electronics laboratories at the University of Science and Technology of Southern Philippines-CDO campus to detect and identify missing components. The study will focus on flip-flop, full-wave, half-wave, and Pre-Amp circuit components to test the accuracy of the detection, despite its limitations in determining exact location, component value, and circuit connection.

2. Material and methods

2.1 Conceptual framework

As shown by Figure 2, the framework uses advanced image processing techniques to automatically identify missing electronic components on a printed circuit board (PCB). This early detection prevents defective boards from advancing to later stages of manufacturing. Automated visual inspection reduces human error and increases efficiency. The framework ensures PCBs are fully populated with all necessary components before assembly or deployment, improving product reliability and minimizing costly repairs or delays.

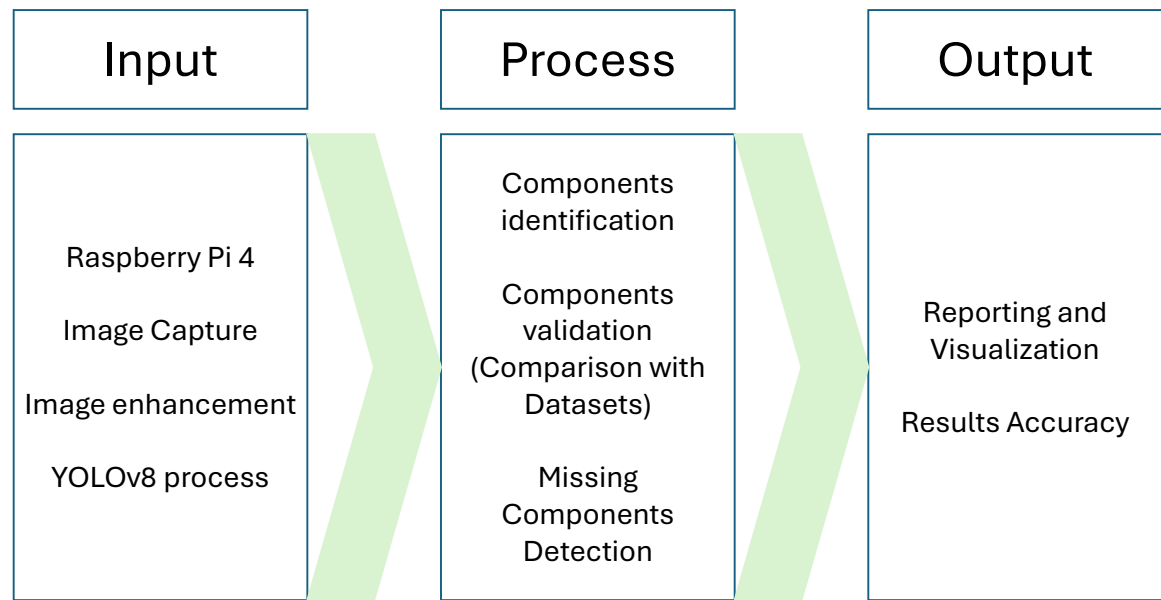


Figure 2. Conceptual framework

2.2 Image subtraction

There are a lot of methods used in detecting defects especially in the manual inspection in PCB, it is time consuming and prone to human error. Although nowadays the PCB manufacturing industries use different image processing methods such as image subtraction, they cannot keep up with the quality inspection process [14].

2.3 Comparison of YOLOv8 with previous Versions (YOLOv4, YOLOv7)

The review highlights the differences between YOLOv8 and its predecessors, such as YOLOv7 and YOLOv4, emphasizing YOLOv8's flexibility and lightweight design, which includes advancements like multiscale prediction and improved object localization [16]. Designed to make object detection more accessible, YOLOv8 requires fewer computational resources while maintaining high-quality results. Its architecture incorporates improved anchor box configurations, enhanced data augmentation techniques, and optimized loss functions, leading to better generalization. YOLOv8 is faster due to architectural improvements, achieves higher mean average precision (mAP) scores in challenging scenarios like low-light or cluttered environments, and features a lightweight structure suitable for deployment on edge devices such as mobile phones and drones. Its application areas include security, retail analytics, and smart cities [17].

In Figure 3. YOLOv8 is one of the recent models in the YOLO family of real-time object detectors, providing cutting-edge speed and accuracy. YOLOv8 builds on the improvements of earlier iterations of YOLO and adds new features and optimizations that make it a great option for a variety of object detection jobs in a broad range of applications.

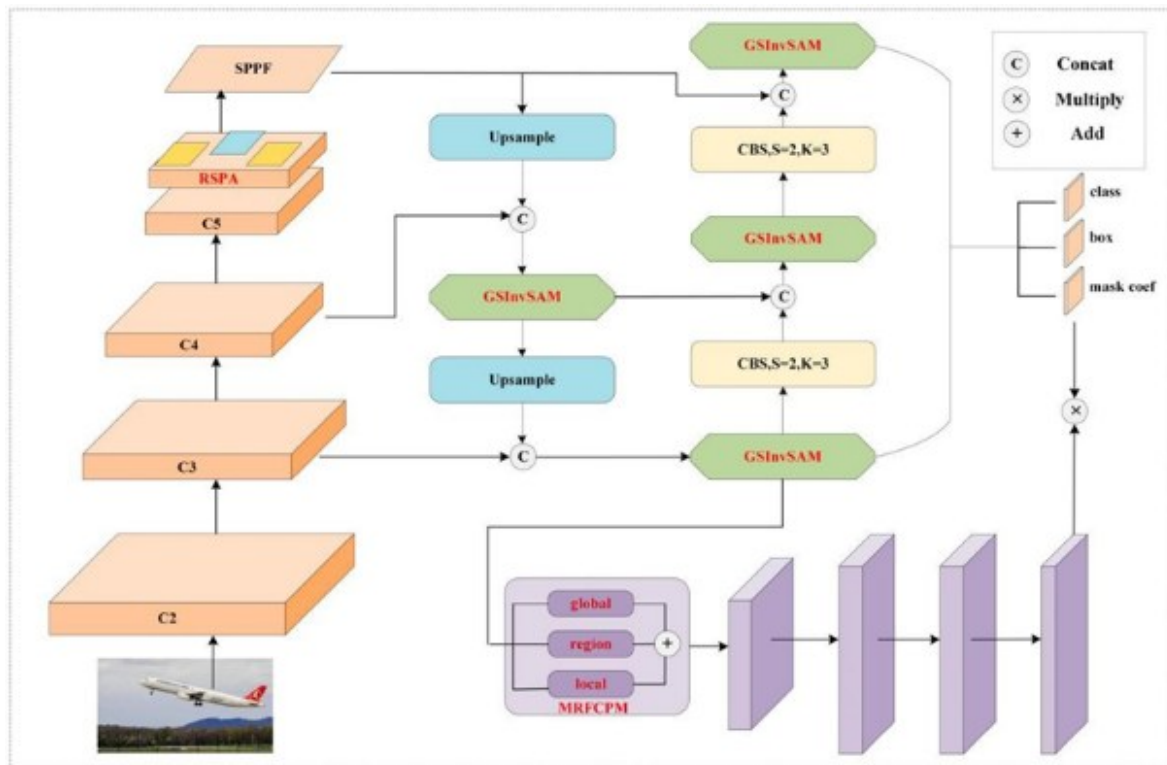


Figure 3. YOLOv8 architecture

2.4 System design

In Figure 4, we can see the detailed 3D system design of the image object detection. The image object detection is designed to detect missing components in the PCB circuit.



Figure 4. System design

2.5 System flowchart

The system starts with four PCB circuit selections: Full Wave Rectifier, Half Wave Rectifier, Flip-flop, and Pre-Amp. The user selects a circuit and feeds an image to the YOLOv8 model for circuit detection. If the model fails to detect the components, the process returns to the camera interface. The YOLOv8 compares the detected components to the ground truth or the correct list of a circuit based on the selected circuit. If the detected components match the ground truth, the system displays "CORRECT" confirming the circuit is correct. If there are exceeding or missing components, the system lists them for the user to identify. The system also offers the option to retry the inspection, allowing users to address any issues and repeat the process to ensure the PCB is assembled correctly. This method of image object detection PCB inspection offers a solution to quality control in electronics technology, especially for individuals using basic detection where component placement is crucial to circuit functionality.

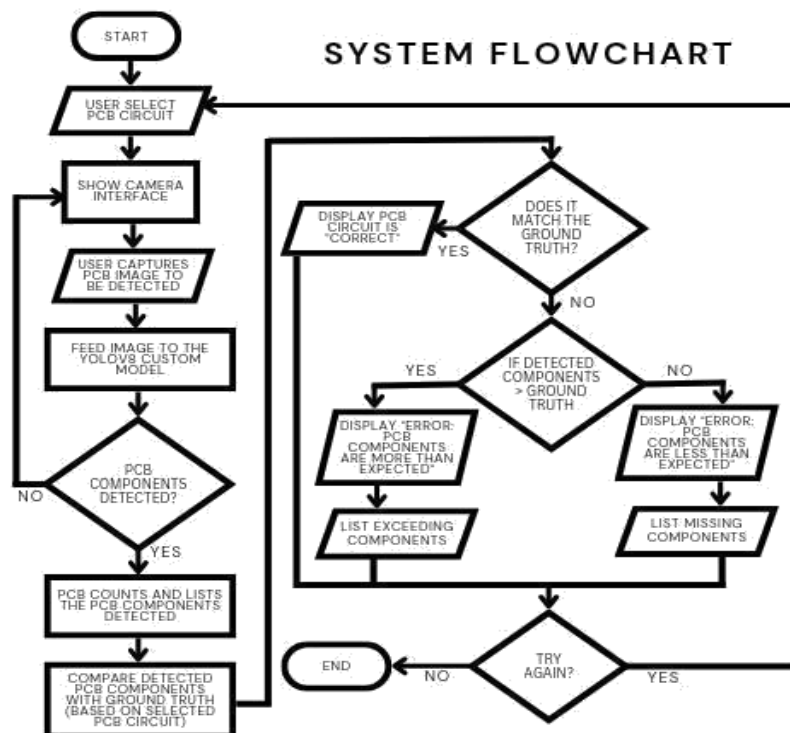


Figure 5. Flowchart

2.6 AI model process flowchart

As shown by Figure 6, it shows the artificial intelligence model process flowchart. This flowchart demonstrates the systematic processes from data collection, data processing, model selection, model training, model evaluation, model tuning, model testing, model deployment and maintenance/improvement which are involved in implementing AI solutions.

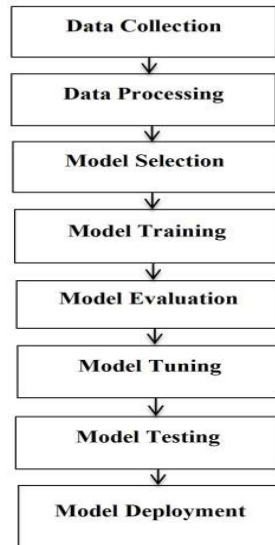


Figure 6. Artificial intelligence model process flowchart

2.7 System architecture

In Figure 7 we can see a detailed illustration of the image object detector, along with its label and description. It is designed to detect missing components, specifically in printed circuit boards (flip-flop, full-wave rectifier, half-wave rectifier, and Pre-Amp).



Figure 7. Image object detector labeling

2.8 Research design

This study used a survey questionnaire to gather user perceptions of accuracy, functionality, reliability, and user-friendliness among electronics students and technicians at the University of Science and Technology of Southern Philippines-CDO. The sample size was 47, chosen through random sampling. The questionnaire, categorized as open-ended or closed-ended, aimed to gather data on opinions.

2.9 Wireframe design

The system will be packaged as a software, consisting of a GUI and an AI model using YOLOv8 Nano from Ultralytics. The GUI is coded using Python's Tkinter library, while YOLO is a popular AI model for object detection on edge devices like Raspberry Pi. The wire-frame design serves as the software's blueprint, with a Start Page and Camera Preview Page for user interaction.

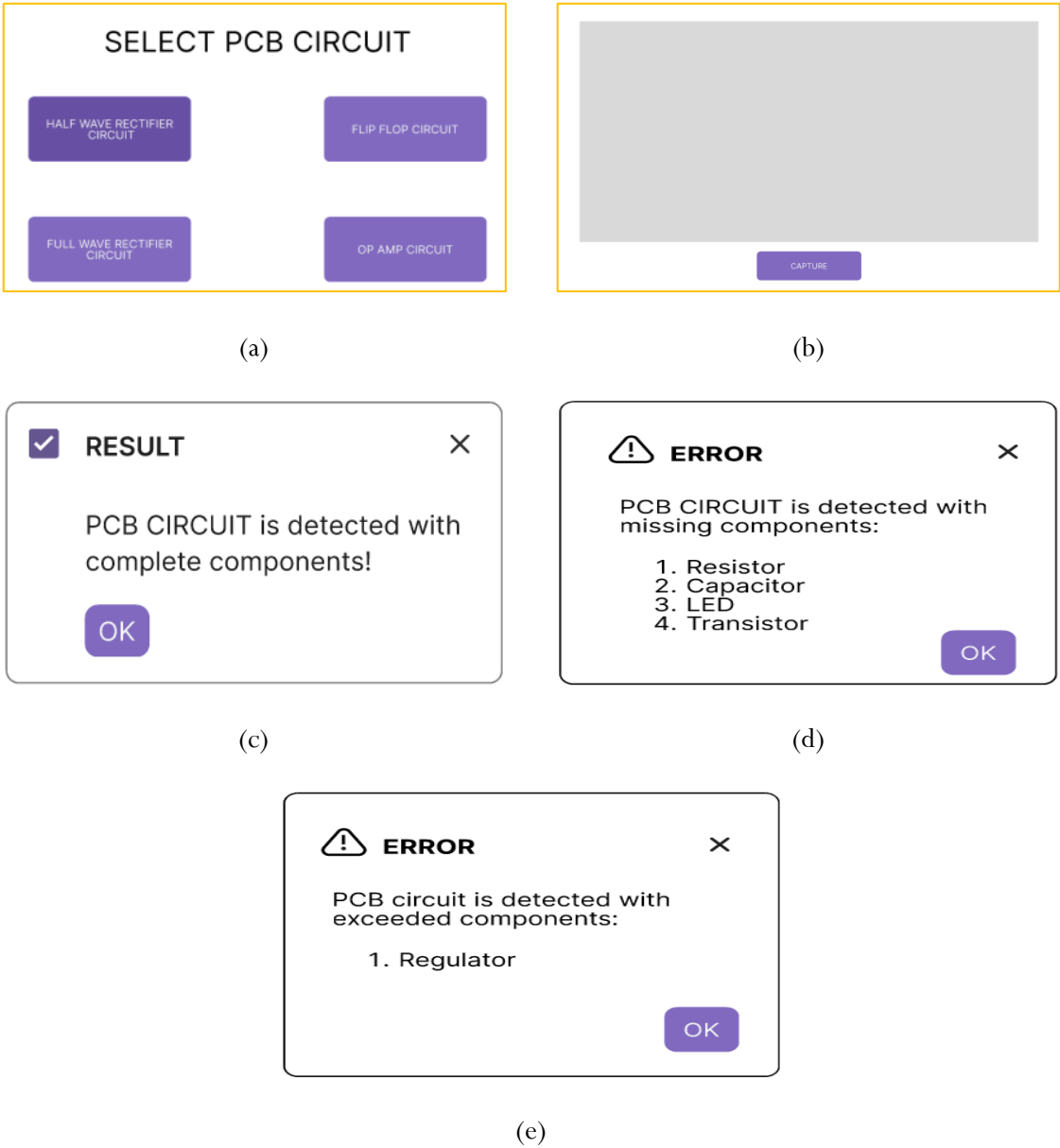


Figure 8. (a) Start page, (b) Camera view, (c) Complete PCB circuit message box, (d) Missing components missing box, and (e) Exceeded components message box

2.10 Predefined PCB components list

Table 1 displays the PCB components in four defined circuits, serving as a reference and ground truth list. The model detects and enumerates these components, then compares them to predefined circuits. Depending on the comparison, it displays a message box, indicating whether the detected list is equal

to the predefined list, missing components are present in the predefined list, or components exceed the predefined list.

Table 1. Predefined PCB components list: Ground truth

PCB Circuit	Qty.	Component Type
Half Wave Rectifier	x1	rectifier
	x1	resistor
Full Wave Rectifier	x4	rectifier
	x1	resistor
	x1	capacitor
	x2	LED
Flip Flop Circuit	x4	resistor
	x2	capacitor
	x2	transistor
	x9	resistor
Pre-Amp Circuit	x5	capacitor
	x2	transistor

2.11 Instrument

To evaluate the quality of the system, a five-point Likert scale was used, covering aspects such as accuracy, functionality, reliability, and user-friendliness. Table 2 presents the scale range, numerical values, and the adjectival descriptions used in the assessment.

Table 2. Likert scale for evaluating system quality

Scale	Indication	Description
5	Very effective	The system is highly regarded for its excellent performance in identifying small components on PCBs, with stable operation and no malfunctions. It effectively generalizes across various PCB types, detecting components accurately. The system is dependable, stable, and user friendly, with most respondents finding it easy to navigate and visually appealing.
4	Effective	The system is overall effective, offering reliable performance in identifying small components on printed circuit boards (PCBs) with stable operation and no major malfunction. It effectively generalizes across various PCB circuit types, consistently detecting components accurately. The system is dependable and meets stability conditions. While generally responsive, some minor delays were noted, indicating potential for improvement.
3	Neutral	The system's reliability is moderate, with occasional glitches that may slightly interface with its overall performance. Maintenance is needed more often than anticipated, but it remains manageable and does not significantly affect its operation.
2	Ineffective	The system's overall performance is failing to meet the established expectations. Several malfunctions have been identified, which are affecting its functionality and efficiency.
1	Very ineffective	The system's overall performance is rated very poorly, indicating significant issues in its functionality and effectiveness. The malfunctions observed are causing considerable disruption and are a major concern in terms of reliability.

3. Results and discussion

This research aimed to develop a system using computer vision to identify if PCB circuit components are complete or incomplete. The system was designed to distinguish between different PCB components and identify missing ones. The researchers created a YOLO-based detection system, a user-friendly GUI, and evaluated its effectiveness through various scenarios and datasets. The system's performance was evaluated through system architecture and a systematic comparison of detected components against predefined ground truth lists.

The system uses Python Tkinter and YOLOv8 to detect PCB components, with the user selecting the circuit to detect. The dataset collected was annotated with a dataset split of 70-20-10, with 70% for training, 20% for validation, and 10% for testing. The dataset consisted of 3,422 images divided into three subsets for model training and evaluation. The model was optimized for precision and accuracy by fine-tuning hyperparameters, such as learning rate and learning rate. The system's effectiveness was evaluated through system architecture and system evaluations.

4.1 Confusion matrix (testing dataset)

In Figure 9, training accuracy was achieved using over 3000 annotated images, with strong accuracy across five classes during the testing phase, involving 341 images.

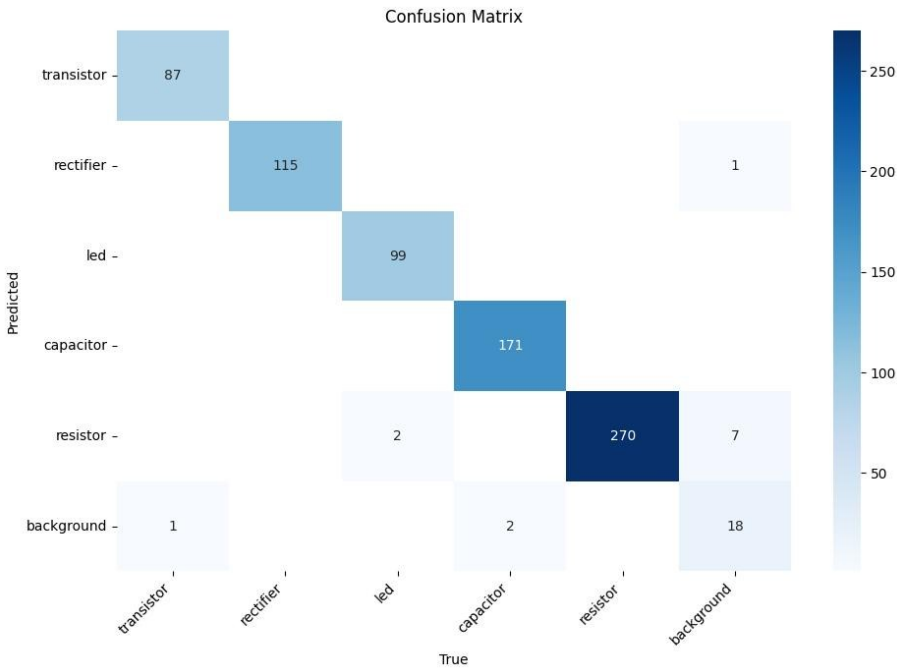


Figure 9. Shows the confusion matrix during training and testing of datasets

1.1 Confusion matrix normalized (testing dataset)

Figure 10 shows normalized image processing for detecting missing components on PCBs. The model performs well in 99% and 100% accuracy for transistors, 98% and 99% accuracy for LEDs, and 99% accuracy for capacitors. However, it struggles with resistors and misclassifies some components. The confusion matrix shows strong performance for most classes but suggests areas for improvement, particularly for resistors.

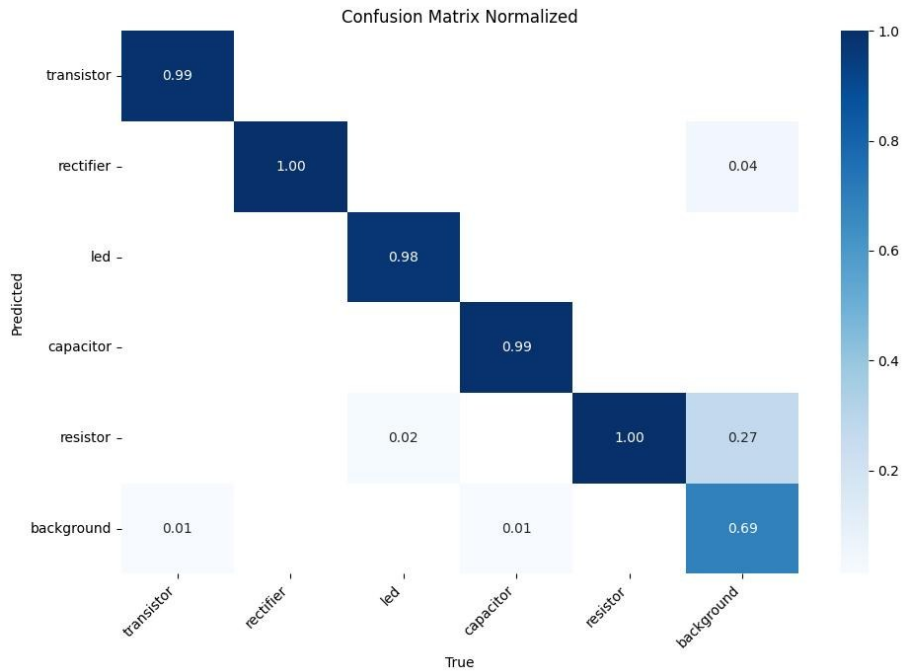


Figure 10. Shows the confusion matrix normalized during training and testing of datasets

The dataset is imbalanced, with background being the least frequent and resistor being the most frequent. The resistor has the highest weights, requiring less adjustment for model focus. The background has the lowest weight, requiring more attention for accurate classification.

Table 3. Shows the support and weights per class

Class	Support (Ni)	Weights
Transistor	88	0.1138
Rectifier	115	0.1487
LED	101	0.1306
Capacitor	173	0.2238
Resistor	270	0.3492
Background	26	0.0336
Total Instances (N)	773	

1.2 Weighted average calculation

The classifier's performance was evaluated across all classes, considering varying class sizes. The average precision weight was 98.2%, recall was 98.3%, and f1-score was 98.2%. The classifier achieved high accuracy in positive predictions but might miss some. The f1-score was 0.9824, indicating a balanced performance between precision and recall. However, there is room for improvement in capturing all positive instances, potentially through fine-tuning parameters or incorporating additional features.

Table 4. Evaluation of the classifier's performance across

Multiclass classification	Weighted precision	Weighted recall	Weighted F1-score	Total instances (N)
Weighted. avg	98.2353%	98.2894%	98.2499%	773

1.3 Multiclass classification accuracy

In Table 5, the proposed model achieved a multiclass accuracy of 98.3%, correctly classifying 98% of instances across 341 images in the confusion matrix, demonstrating its effectiveness and reliability in complex classification tasks.

Table 4. Accuracy of total instances of the different class

Class	True positive (TP)	Instances
Transistor	87	88
Rectifier	115	115
LED	99	101
Capacitor	171	173
Resistor	270	270
Background	18	26
Total	760	773

1.4 Summary of prototype evaluation

The evaluation parameters involve accuracy, functionality, reliability, and user-friendly of the prototype. The results are shown below in Table 5, for accuracy the average mean is 4.8 with a standard deviation of 0.94. For prototype's functionality the mean average is 4.7 with a standard deviation of 0.94. Also, for prototype's reliability it has a mean average of 4.8 with a standard deviation of 0.91. And lastly, for the prototype's user-friendly it has a mean average of 4.7 with a standard deviation of 0.94.

Table 5. Shows the evaluation parameters involve accuracy, functionality, reliability, and user-friendly of the prototype

Parameter	Mean	Standard deviation
Accuracy		
System accurately detects missing components on PCB's (e.g., Pre-Amps, Flip-flops, Rectifiers)	4.91	0.98
Accurately identifies specific components (e.g., Pre-Amps, Flip-flops, Rectifiers) on the PCB	4.66	0.93
Average	4.80	0.96
Functionality		
Ability to detect small components (Pre-Amp, Flip-flop, Rectifiers).	4.80	0.96
Works across different PCB design (Pre-Amp, Flip-flop, Rectifiers)	4.50	0.90
Average	4.70	0.94
Reliability		
Stable during use (i.e., no crashes or significant issues)	4.97	0.97
Reliable in detecting components without errors	4.67	0.92
Average	4.80	0.91
User friendly		
System's interface is visually clear and easy to understand	4.60	0.92
Responds quickly to user inputs	4.81	0.96
Average	4.70	0.94
Total average	4.80	0.94

5 Conclusion

Researchers at the University of Science and Technology of Southern Philippines-CDO found a system that accurately detects missing components and identifies their names, achieving an 80% accuracy in top view of a PCB. However, it struggles with side views. The system achieved a multiclass accuracy of 98.3%, classifying 98% of instances across a dataset of 341 images. The system also demonstrated high performance in specific configurations, with an average user evaluation score of 4.8. Researchers developed a YOLO-based detection system for complex PCB layouts, demonstrating strong performance in identifying missing components and accurately distinguishing between different components. As a result of the study conducted, the researchers provided some recommendations to further enhance the device:

- 1) When using a Raspberry Pi camera to detect missing components on printed circuit boards, it's essential to restrict the size of the printed circuit boards to a maximum length of 2cm and a width of 3cm. Exceeding these dimensions can lead to blurriness, making it difficult for the camera to capture clear images necessary for accurate detection. By adhering to these size limits, you can ensure optimal image clarity and effective component identification during inspections.
- 2) To enhance the detection system for missing components on printed circuit boards and ensure precise detection of missing components and their corresponding value, the researchers recommend this improvement as it will lead to greater accuracy and efficiency in the detection process.

Author's declaration

Author contribution

Dominic O. Cagadas and **Christine Marie J. Madrid** led the conceptualization and methodology design of the study, supervised the research process, and contributed to data visualization and software development. **Janine T. Neri**, **Joebert T. Osin**, **Marjo May T. Oro**, and **Bhea Blair A. Sappal** were primarily responsible for data collection, curation, formal analysis, and drafting the initial manuscript. All authors participated in reviewing and editing the manuscript, managing the submission process, and approved the final version for publication

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Data availability

The datasets collected and analyzed are not publicly available due to the ongoing improvement of the system.

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Conflict of interest

The authors declare no competing interests.

Ethical clearance

This study does not involve human participants as research subjects and therefore did not require ethical approval.

AI statements

This article is the original work of the authors without using AI tools for writing sentences and/or creating/editing table and figures in this manuscript.

Publisher's and Journal's Note

Researcher and Lecturer Society as the publisher, and the Editor of Innovation in Engineering state that there is no conflict of interest towards this article publication.

References

- [1] I. Grout, "PCB Design," in *Digital Systems Design with FPGAs and CPLDs*, Elsevier, 2008, pp. 123–176. <https://doi.org/10.1016/B978-0-7506-8397-5.00003-9>
- [2] R. Dallaev, T. Pisarenko, N. Papež, P. Sadovský, and V. Holcman, "A Brief Overview on Epoxies in Electronics: Properties, Applications, and Modifications," *Polymers (Basel)*, vol. 15, no. 19, p. 3964, Sep. 2023, <https://doi.org/10.3390/polym15193964>
- [3] Y. Sun, Z. Sun, and W. Chen, "The evolution of object detection methods," *Eng Appl Artif Intell*, vol. 133, p. 108458, Jul. 2024, <https://doi.org/10.1016/j.engappai.2024.108458>
- [4] C.-Y. Huang and P.-X. Tsai, "Applying Machine Learning to Construct a Printed Circuit Board Gold Finger Defect Detection System," *Electronics (Basel)*, vol. 13, no. 6, p. 1090, Mar. 2024, <https://doi.org/10.3390/electronics13061090>
- [5] A. K. Kausik, A. Bin Rashid, R. F. Baki, and M. M. Jannat Maktum, "Machine learning algorithms for manufacturing quality assurance: A systematic review of performance metrics and applications," *Array*, vol. 26, p. 100393, Jul. 2025, <https://doi.org/10.1016/J.ARRAY.2025.100393>
- [6] L. Farahzadi, I. Odeh, M. Kioumars, and B. Shafei, "Automated image-based condition assessment of the built environment: A state-of-the-art investigation of damage characteristics and detection requirements," *Results in Engineering*, vol. 26, p. 104978, Jun. 2025, <https://doi.org/10.1016/J.RINENG.2025.104978>
- [7] H. Zhang, Y. Li, D. M. Sharid Kayes, Z. Song, and Y. Wang, "Research on PCB defect detection algorithm based on LPCB-YOLO," *Front Phys*, vol. 12, Jan. 2025, <https://doi.org/10.3389/fphy.2024.1472584>
- [8] Z. He, Y. Lian, Y. Wang, and Z. Lu, "A comprehensive review of research on surface defect detection of PCBs based on machine vision," *Results in Engineering*, vol. 27, p. 106437, Sep. 2025, <https://doi.org/10.1016/J.RINENG.2025.106437>
- [9] L. Liu, H. Gong, Y. Zhou, A. Zhou, and L. Cong, "A YOLO-based network with dynamic feature pyramid for multi-scale bridge surface defect detection," *International Journal of Transportation Science and Technology*, Jan. 2025, <https://doi.org/10.1016/J.IJTST.2025.01.004>

- [10] X. Zhang, Y. Gao, H. Wang, and Q. Wang, "Improve YOLOv3 using dilated spatial pyramid module for multi-scale object detection," *Int J Adv Robot Syst*, vol. 17, no. 4, Jul. 2020, <https://doi.org/10.1177/1729881420936062>
- [11] M. L. Ali and Z. Zhang, "The YOLO Framework: A Comprehensive Review of Evolution, Applications, and Benchmarks in Object Detection," *Computers*, vol. 13, no. 12, p. 336, Dec. 2024, <https://doi.org/10.3390/computers13120336>
- [12] B. Zhang *et al.*, "Multi-Feature Fusion YOLO Approach for Fault Detection and Location of Train Running Section," *Electronics (Basel)*, vol. 14, no. 17, p. 3430, Aug. 2025, <https://doi.org/10.3390/electronics14173430>
- [13] G. Xiao, S. Hou, and H. Zhou, "PCB defect detection algorithm based on CDI-YOLO," *Sci Rep*, vol. 14, no. 1, p. 7351, Mar. 2024, <https://doi.org/10.1038/s41598-024-57491-3>
- [14] S. Chen, X. Liang, and W. Jiang, "PCB Defect Detection Based on Image Processing and Improved YOLOv5," *J Phys Conf Ser*, vol. 2562, no. 1, p. 012002, Aug. 2023, <https://doi.org/10.1088/1742-6596/2562/1/012002>
- [15] J. Y. Lim, J. Y. Lim, V. M. Baskaran, and X. Wang, "A deep context learning based PCB defect detection model with anomalous trend alarming system," *Results in Engineering*, vol. 17, p. 100968, Mar. 2023, <https://doi.org/10.1016/J.RINENG.2023.100968>
- [16] Y. Tang, R. Liu, and S. Wang, "YOLO-SUMAS: Improved Printed Circuit Board Defect Detection and Identification Research Based on YOLOv8," *Micromachines (Basel)*, vol. 16, no. 5, p. 509, Apr. 2025, <https://doi.org/10.3390/mi16050509>
- [17] V. A. Adibhatla, J.-S. Shieh, M. F. Abbod, H.-C. Chih, C.-C. Hsu, and J. Cheng, "Detecting Defects in PCB using Deep Learning via Convolution Neural Networks," in *2018 13th International Microsystems, Packaging, Assembly and Circuits Technology Conference (IMPACT)*, IEEE, Oct. 2018, pp. 202–205. <https://doi.org/10.1109/IMPACT.2018.8625828>